JC02 Rec'd PCT/PTO 2 6 FEB 2001

FORM PTO-1390 REV. 5-93 US DEPARTMENT OF COMMERCE PATENT AND TRADEMARK OFFICE **TRANSMITTAL LETTER TO THE UNITED STATES DESIGNATED/ELECTED OFFICE (DO/EO/US) CONCERNING A FILING UNDER 35 U.S.C. 371**		ATTORNEYS DOCKET NUMBER **P00,1993** U.S.APPLICATION NO. (if known, see 37 CFR 1.5) 09/763772
INTERNATIONAL APPLICATION NO. **PCT/DE99/01949**	INTERNATIONAL FILING DATE 1 July 1999	PRIORITY DATE CLAIMED 25 August 1998

TITLE OF INVENTION
"METHOD FOR TRAINING A NEURAL NETWORK, METHOD FOR CLASSIFYING A SEQUENCE OF INPUT PARAMETERS USING A NEURAL NETWORK, NEURAL NETWORK AND ARRAY FOR TRAINING A NEURAL NETWORK"

APPLICANT(S) FOR DO/EO/US
Gustavo DECO AND Bernd SCHÜRMANN

Applicant herewith submits to the United States Designated/Elected Office (DO/EO/US) the following items and other information:

1. ☒ This is a **FIRST** submission of items concerning a filing under 35 U.S.C. 371.
2. ☐ This is a **SECOND** or **SUBSEQUENT** submission of items concerning a filing under 35 U.S.C. 371.
3. ☒ This express request to begin national examination procedures (35 U.S.C. 371(f)) at any time rather than delay.
4. ☒ A proper Demand for International Preliminary Examination was made by the 19th month from the earliest claimed priority date.

5. ☒ A copy of International Application as filed (35 U.S.C. 371(c)(2))
   a. ☒ is transmitted herewith (required only if not transmitted by the International Bureau).
   b. ☐ has been transmitted by the International Bureau.
   c. ☐ is not required, as the application was filed in the United States Receiving Office (RO/US)
6. ☒ A translation of the International Application into English (35 U.S.C. 371(c)(2).

7. ☒ Amendments to the claims of the International Application under PCT Article 19 (35 U.S.C. §371(c)(3))
   a. ☐ are transmitted herewith (required only if not transmitted by the International Bureau).
   b. ☐ have been transmitted by the International Bureau.
   c. ☐ have not been made; however, the time limit for making such amendments has NOT expired.
   d. ☒ have not been made and will not be made.

8. ☐ A translation of the amendments to the claims under PCT Article 19 (35 U.S.C. 371(c)(3)).

9. ☒ An oath or declaration of the inventor(s) (35 U.S.C. 371(c)(4)).)

10. ☐ A translation of the annexes to the International Preliminary Examination Report under PCT Article 36 (35 U.S.C.371(c)(5)).

Items 11. to 16. below concern other document(s) or information included:

11. ☒ An Information Disclosure Statement under 37 C.F.R. 1.97 and 1.98; **(PTO 1449, Prior Art, Search Report).**

12. ☒ An assignment document for recording. A separate cover sheet in compliance with 37 C.F.R. 3.28 and 3.31 is included. **(SEE ATTACHED ENVELOPE)**

13. ☒ A FIRST preliminary amendment.
    ☐ A SECOND or SUBSEQUENT preliminary amendment.

14. ☒ A substitute specification & marked up version of application.

15. ☒ A change of power of attorney and/or address letter.

16. ☒ Other items or information:
    a. ☒ Submittal of Drawings
    b. ☒ **EXPRESS MAIL #EL 655301196US, dated February 26, 2001.**

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U.S. APPLICATION NO. (if known, see 37 C.F.R. 1.5)	INTERNATIONAL APPLICATION NO.	ATTORNEY'S DOCKET NUMBER
09/763772	PCT/DE99/01949	P00,1993

				CALCULATIONS	PTO USE ONLY
17. ☒ The following fees are submitted: **BASIC NATIONAL FEE (37 C.F.R. 1.492(a)(1)-(5):** Search Report has been prepared by the EPO or JPO . . . . $860.00 International preliminary examination fee paid to USPTO (37 C.F.R. 1.482) . . $700.00 No international preliminary examination fee paid to USPTO (37 C.F.R. 1.482) but international search fee paid to USPTO (37 C.F.R. 1.445(a)(2) . . . . $770.00 Neither international preliminary examination fee (37 C.F.R. 1.482) nor international search fee (37 C.F.R. 1.445(a)(2) paid to USPTO . . . . $1040.00 International preliminary examination fee paid to USPTO (37 C.F.R. 1.482) and all claims satisfied provisions of PCT Article 33(2)-(4) . . . . $ 96.00					
ENTER APPROPRIATE BASIC FEE AMOUNT =				$ 860.00	
Surcharge of $130.00 for furnishing the oath or declaration later than ☐ 20 ☐ 30 months from the earliest claimed priority date (37 C.F.R. 1.492(e)).				$	
Claims	Number Filed	Number Extra	Rate		
Total Claims	16 - 20 =		X $ 18.00	$	
Independent Claims	4 - 3 =	1	X $ 80.00	$ 80.00	
Multiple Dependent Claims			$270.00 +	$	
TOTAL OF ABOVE CALCULATIONS =				$ 860.00	
Reduction by 1/2 for filing by small entity, if applicable. Verified Small Entity statement must also be filed. (Note 37 C.F.R. 1.9, 1.27, 1.28)				$	
SUBTOTAL =				$ 940.00	
Processing fee of $130.00 for furnishing the English translation later than ☐ 20 ☐ 30 months from the earliest claimed priority date (37 CFR 1.492(f)). +				$	
TOTAL NATIONAL FEE =				$ 940.00	
Fee for recording the enclosed assignment (37 C.F.R. 1.21(h). The assignment must be accompanied by an appropriate cover sheet (37 C.F.R. 3.28, 3.31). $40.00 per property +					
TOTAL FEES ENCLOSED =				$ 940.00	
				Amount to be refunded	$
				charged	$

a. ☒ A check in the amount of $ 940.00 to cover the above fees is enclosed.

b. ☐ Please charge my Deposit Account No. ________ in the amount of $ ______ to cover the above fees. A duplicate copy of this sheet is enclosed.

c. ☒ The Commissioner is hereby authorized to charge any additional fees which may be required, or credit any overpayment to Deposit Account No. 501519. A duplicate copy of this sheet is enclosed.

NOTE: Where an appropriate time limit under 37 C.F.R. 1.494 or 1.495 has not been met, a petition to revive (37 C.F.R. 1.137(a) or (b)) must be filed and granted to restore the application to pending status.

SEND ALL CORRESPONDENCE TO:

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SIGNATURE

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NAME

31,870
Registration Number

IN THE UNITED STATES ELECTED OFFICE
OF THE UNITED STATES PATENT AND TRADEMARK OFFICE
UNDER THE PATENT COOPERATION TREATY-CHAPTER II

"**PRELIMINARY AMENDMENT**"

APPLICANT: Gustavo DECO et al.

SERIAL NO.: EXAMINER:

FILING DATE: ART UNIT:

INTERNATIONAL APPLICATION NO.: PCT/DE99/01949

INTERNATIONAL FILING DATE: 1 July 1999

INVENTION: METHOD FOR TRAINING A NEURAL NETWORK, METHOD FOR CLASSIFYING A SEQUENCE OF INPUT PARAMETERS USING A NEURAL NETWORK, NEURAL NETWORK AND ARRAY FOR TRAINING A NEURAL NETWORK

Hon. Assistant Commissioner for Patents
Box PCT
Washington D.C. 20231

SIR:

Amend the above-identified international application before entry into the national stage before the U.S. Patent & Trademark Office under 35 U.S.C. §371 as follows:

IN THE SPECIFICATION

An amended substitute specification is attached, and a marked up copy of the original specification showing the changes is also enclosed.

IN THE CLAIMS

Amend the claims as shown in the following replacement claims, the marked up version of which is attached following the marked up specification.

We Claim:

1. A method for training a neural network that contains pulsed neurons,

a) training the neural network for a first time span such that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) forming the discrimination value dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) implementing the following steps interactively:

shortening the first time span to form a second time span,

forming a second discrimination value for the second time span,

when the second discrimination value is the same as the first discrimination value, then performing a new iteration with a new second time span that is formed by shortening the second time span of the preceding iteration,

otherwise, ending the method and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

2. A method according to claim 1, wherein an optimization method that is not gradient based is utilized for the maximization of at least one of the first discrimination value and of the second discrimination value.

3. A method according to claim 2, wherein the optimization method is based on the ALOPEX method.

4. A method according to claim 1, whereby the first discrimination value I(T) satisfies the following rule:

$$I(T) = I\left(s; \left\{\begin{matrix} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{matrix}\right\}\right),$$

wherein

- s references the input quantities,
- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],
- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T], and
- N references a plurality of pulsed neurons contained in the neural network.

5. A method according to claim 4, wherein the first discrimination value I(T) satisfies the following rule:

$$I(T) = -\int p(out) \cdot \ln(p(out))dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)} + \\ + \sum_{j=1}^{s} p_j \int p\left(out \middle| s^{(j)}\right) \cdot \ln\left(p\left(out \middle| s^{(j)}\right)\right) dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)}$$

with

$$p(out) = \sum_{j=1}^{s} p_j p\left(out \middle| s^{(j)}\right),$$

wherein

- $s^{(j)}$ references an input quantity that is applied to the neural network at a time j,
- p_j references a probability that the input quantity $s^{(j)}$ is applied to the neural network at a pint in time j,
- $p(out|s^{(j)})$ references a conditioned probability that a pulse is generated by a pulsed neuron in the neural network under the condition that the input quantity $s^{(j)}$ is applied to the neural network at a point in time j.

6. A method according to claim 1, wherein the training sequence of inputs quantities are is of measured physical signals.

7. A method according to claim 6, wherein the training sequence of input quantities is signals of an electroencephalogram.

8. A method for classification of a sequence of input quantities upon employment of a neural network that contains pulsed neurons and was trained, comprising to the following steps:

a) training the neural network for a first time span such that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) forming the discrimination value dependent on pulses that are formed by the pulsed neurons within a first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) implementing the following steps interactively:
shortening the first time span to form a second time span,
forming a second discrimination value for the second time span,
when the second discrimination value is the same as the first discrimination value, then performing a new iteration with a new second time span that is formed by shortening the second time span of the preceding iteration,
otherwise, ending the method and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value,

supplying the sequence of input quantities to the neural network; and
forming a classification signal that indicates what kind of sequence of input quantities the supplied sequence is.

9. A method according to claim 9, wherein the training sequence of input quantities and the sequence of input quantities are measured physical signals.

10. A method according to claim 9, wherein the training sequence of input quantities and the sequence of input quantities are measured signals of an electroencephalogram.

11. A neural network that contains pulsed neurons has been trained according to the following steps:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

the first time span is shortened to form a second time span,

a second discrimination value is formed for the second time span,

when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

12. A neural network according to claim 10, wherein the network is utilized for classification of a physical signal.

13. A neural network according to claim 10, utilized for the classification of an electroencephalogram signal.

14. An arrangement for training a neural network that contains pulsed neurons comprising:

a processor that is configured such that the following steps implemented:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:
the first time span is shortened to form a second time span,
a second discrimination value is formed for the second time span,
when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration, and
otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

15. An arrangement according to claim 14, wherein the network is utilized for the classification of a physical signal.

16. An arrangement according to claim 14, wherein the network is utilized for the classification of a signal of an electroencephalogram.

REMARKS

The foregoing amendments to the specification and claims under Article 41 of the Patent Cooperation Treaty place the application into a form for prosecution before the U.S. Patent and Trademark Office under 35 U.S.C. §371. Accordingly, entry of these amendments before examination on the merits is hereby requested.

Respectfully submitted,

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ATTORNEY FOR APPLICANT

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4/PRTS

09/763772
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Substitute

SPECIFICATION

TITLE

METHOD FOR TRAINING A NEURAL NETWORK, METHOD FOR THE CLASSIFICATION OF A SEQUENCE OF INPUT QUANTITIES UPON EMPLOYMENT OF A NEURAL NETWORK, NEURAL NETWORK AND ARRANGEMENT FOR THE TRAINING OF A NEURAL NETWORK

BACKGROUND OF THE INVENTION

Field of the Invention

The present invention is directed to a method for training a neural network, to a method for the classification of a sequence of input quantities upon employment of a neural network as well as to a neural network and an arrangement for training a neural network.

Description of the Related Art

A neural network comprises neurons that are at least partially connected to one another. Input neurons of the neural network are supplied with input signals as input quantities supplied to the input neurons. The neural network usually comprises a plurality of layers. A respective neuron generates a signal dependent on input quantities supplied to a neuron of the neural network and on an activation function provided for the neuron, the signal being in turn supplied to neurons of a further layer as an input quantity according to a prescribable weighting. An output quantity dependent on quantities that are supplied to the output neuron of neurons of the preceding layer is generated in an output neuron in an output layer. There are currently essentially two approaches in view of the questions as to the form in which information is stored in a neural network.

A first approach assumes that the information in a neural network is encoded in the spectral domain. Given this approach, a chronological sequence of input quantities is encoded such that a respective input neuron is provided for each time row value of a chronological sequence of the input quantities, the respective time row value being applied to this input neuron.

Given a neural network that is designed according to this approach, a hyperbolic tangent (tanh) is usually employed as an activation function.

This first type of neural network is referred to below as a static neural network.

What is particularly disadvantageous about this approach is that it is not possible with a static neural network to explicitly consider a dynamics of a process subject to a technical system in the internal coding of the sequence of input quantities.

The Time Delay Neural Networks (TDNN) known from German Patent Document DE 195 31 697 C2 attempt to counter this disadvantage in that, given a plurality of sequences of input quantities, a respective input neuron is provided for each sequence and for each time row value. This approach particularly exhibits the disadvantage that the dimension of the input space -- represented by the plurality of input neurons -- increases exponentially with an increasing plurality of different sequences of input quantities to be taken into consideration.

An increasing plurality of neurons in the neural network, moreover, involves an increased training outlay upon employment of a plurality of training data that increases with an increasing plurality of neurons. A training of a static neural network becomes highly calculation-intensive under these conditions or, respectively, can practically no longer be implemented.

A gradient-based training method, for example the back-propagation method, is usually utilized for training a static neural network.

The publication by Unnikrishnan, et al., "Alopex: A Correlation-Based Learning Algorithm for Feedforward and Recurrent Neural Networks", also discloses a training method for a static neural network that is referred to as the ALOPEX method. In this method, the training of a static neural network is viewed as an optimization problem. In this case, the goal of the optimization is a minimization of a error criterion E taking weightings that are present in the static neural network and with which the connections between neurons are weighted into consideration for a predetermined training data set with training data.

A training datum is a tuple that has input quantities, for example state quantities of a technical system or, respectively, boundary conditions that a technical system is subject to and that are supplied to a technical system as well as an output quantity determined under the boundary conditions and that the technical system forms for the input quantities.

The ALOPEX method shall be explained in greater detail later in conjunction with the exemplary embodiment.

A second approach can be seen therein that the information about a system is encoded in the time domain and in the spectral domain. An artificial neural network that does justice to this approach comprises what are referred to as pulsed neurons and is known from the publication by Gerstner, "Time Structure of the Activity in Neural Networks Models".

According to the publication by Deco et al., "Information Transmission and Temporal Code in Central Spiking Neurons", a pulsed neuron is modelled such that the behavior of a pulsed neuron with respect to an external stimulation, which is referred to below as an input quantity, is described by a stochastic differential equation of the Itô type according to the following rule:

$$dV(t) = \left(-\frac{V(t)}{\tau} + \mu\right)dt + \sigma dW(t) + w dS(t). \quad (1)$$

In the rule (1), dW(t) references a standard Wiener process. A predetermined constant τ describes a delay of a membrane potential V(t) of the modelled neuron without an input quantity that is adjacent at the neuron. The model simulates the behavior of a biological neuron. For this reason, a pulsed neuron is also referred to as a biologically oriented neuron.

Further, S(t) references a coupling of the neuron with another neuron, i.e. the following applies:

$$s(t) = \frac{d}{dt} S(t) = \sum_i \delta(t - t_i), \quad (2)$$

whereby t_i references an arrival time at which an external impulse arrives at an input of a neuron. A soma-synaptic intensity is modelled by a synaptic quantity w.

In this model, the pulsed neuron generates a pulse when the membrane potential V(t) reaches a predetermined threshold Θ. After the pulse is generated, the membrane potential V(t) of the neuron is reset to a predetermined initialization potential value V(0).

A time sequence of pulses is thus described according to the following rule:

$$t_0^{'}, \ldots, t_k^{'}, \ldots, \tag{3}$$

and satisfies the following rule:

$$o(t) = \sum_k \delta\left(t - t_k^{'}\right). \tag{4}$$

It is also known from the afore-mentioned Deco et al. publication that, given the assumption of the above-described model for a pulsed neuron, a discrimination value I(T) can be formed that indicates the dependability with which a sequence of input quantities is correctly classified in view of the training data employed for a training of the neural network.

The discrimination value I(T) is dependent on pulses that are formed by the pulsed neurons within a time span [0; T] as well as on a training sequence of input quantities that are supplied to the neural network. The discrimination value I(T) satisfies the following rule:

$$I(T) = I\left(s; \begin{Bmatrix} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{Bmatrix}\right), \tag{5}$$

whereby

- s references the input quantities,

- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],
- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T],
- N references a plurality of pulsed neurons contained in the neural network.

A stochastic differential equation of the Itô type derives for a neural network with a plurality of N neurons described according to the following rule:

$$dV_i(t) = \left(-\frac{V_i(t)}{\tau} + \mu\right)dt + \sigma dW_i(t) + + \sum_{j=1}^{N} w_{ij} \sum_{k} \delta\left(t - t_{k-\Delta_{ij}}^{(j)}\right)dt + I_i(t)dt, \tag{6}$$

whereby

- V_i (t) references a membrane potential of the i^{th} neuron (i = 1, ..., N),
- N references a plurality of neurons contained in the neural network,
- w_{ij} respectively references a weighting of a coupling between the i^{th} and the j^{th} neuron, clearly a synaptic intensity between the neurons i and j,
- Δ_{ij} references a prescribable axional delay of a signal between the neurons i and j,
- $I_i(t)$ references an external stimulation signal of the neuron i.

The German Patent Document DE 195 31 967C2 discloses a training method for a neural network. Given this method, the neural network is linked in a control circuit with the model of a technical system such that the neural network outputs at least one manipulated variable to the model as an output quantity, and the model generates at least one regulating variable from the manipulated quantity supplied by the neural network, the at least one regulating variable being supplied to the neural network as an input quantity. The regulating variable is superimposed with a noise having a known noise distribution before it is supplied to the model. As a reaction to the regulating variable modified by the impressed noise, the weightings of the neural

network are set as follows: A cost function evaluates whether the change in weighting at the network has effected an improvement of the regulating variable with respect to a rated behavior of the model, and such weightings are favored by the cost function.

SUMMARY OF THE INVENTION

The present invention is based on providing a method as well as an arrangement for training a neural network having pulsed neurons. The invention is also based on providing a method for the classification of a sequence of input quantities upon employment of a neural network having pulsed neurons as well as specifying a neural network having pulsed neurons.

The problems are solved by the methods and the arrangement as well as by the neural network trained according to a method for training a neural network that contains pulsed neurons,

a) the neural network is trained such for a first time span [0; T] that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

- the first time span is shortened to form a second time span,
- a second discrimination value is formed for the second time span,
- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,
- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

In the preferred method, an optimization method that is not gradient based is utilized for the maximization of the first discrimination value and/or of the second discrimination value. The optimization method may be based on the ALOPEX method.

According to one aspect of the invention, the first discrimination value I(T) satisfies the following rule:

$$I(T) = I\left(s; \begin{Bmatrix} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{Bmatrix}\right),$$

whereby

- s references the input quantities,
- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],
- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T], and
- N references a plurality of pulsed neurons contained in the neural network.

The first discrimination value I(T) in a preferred embodiment satisfies the following rule:

$$I(T) = -\int p(out) \cdot \ln(p(out))dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)} + \\ + \sum_{j=1}^{S} p_j \int p\left(out \middle| s^{(j)}\right) \cdot \ln\left(p\left(out \middle| s^{(j)}\right)\right) dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)}$$

with

$$p(out) = \sum_{j=1}^{S} p_j p\left(out \middle| s^{(j)}\right),$$

whereby

- $s^{(j)}$ references an input quantity that is applied to the neural network at a time j,
- p_j references a probability that the input quantity $s^{(j)}$ is applied to the neural network at a pint in time j,
- $p(out|s^{(j)})$ references a conditioned probability that a pulse is generated by a pulsed neuron in the neural network under the condition that the input quantity $s^{(j)}$ is applied to the neural network at a point in time j.

According to the foregoing, the training sequence of inputs quantities is measured physical signals, in particular, the training sequence of input quantities is signals of an electroencephalogram.

The present invention provides a method for the classification of a sequence of input quantities upon employment of a neural network that contains pulsed neurons and was trained according to the following steps:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:
   - the first time span is shortened to form a second time span,
   - a second discrimination value is formed for the second time span,
   - when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,
   - otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value,

-- whereby the sequence of input quantities is supplied to the neural network;

- whereby a classification signal is formed that indicates what kind of sequence of input quantities the supplied sequence is.

In the preferred embodiment, the training sequence of input quantities and the sequence of input quantities are measured physical signals, for example, measured signals of an electroencephalogram.

The present invention also provides a neural network that contains pulsed neurons has been trained according to the following steps:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

- the first time span is shortened to form a second time span,

- a second discrimination value is formed for the second time span,

- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

The neural network is utilized for the classification of a physical signal, such as classification of a signals of an electroencephalogram.

An arrangement for training a neural network that contains pulsed neurons comprises a processor that is configured such that the following steps can be implemented:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

- the first time span is shortened to form a second time span,

- a second discrimination value is formed for the second time span,

- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

The arrangement may be utilized for the classification of a physical signal, such as for the classification of a signal of an electroencephalogram.

A method for training a neural network that contains pulsed neurons comprises the following steps:

a) the neural network is trained for a first time span such that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

A method for the classification of a sequence of input quantities upon employment of a neural network that contains pulsed neurons and was trained according to the following steps comprises the following steps:

a) the neural network is trained for a first time span such that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value,

-- the sequence of input quantities is supplied to the neural network;

d) a classification signal is formed that indicates what kind of sequence of input quantities the supplied sequence is.

A neural network that contains pulsed neurons has been trained according to the following steps:

a) the neural network is trained for a first time span such that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

An arrangement for training a neural network that contains pulsed neurons comprises a processor that is configured such that the following steps can be implemented:

a) the neural network is trained for a first time span such that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

The invention makes it possible to classify a time sequence of input quantities with a neural network what contains pulsed neurons, whereby it is assured that, given optimized classification dependability, a minimized plurality of time values must be supplied to the neural network for classification.

Preferred developments of the invention INSERT DEPENDENT CLAIMS.

An optimization method that is not gradient based is preferably employed for the maximization of the first discrimination value and/or the second discrimination value, preferably an optimization method based on the ALOPEX method.

The first discrimination value preferably satisfies the following rule:

$$I(T) = I\left(s; \left\{\begin{matrix} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{matrix}\right\}\right), \quad (7)$$

whereby

- s references the input quantities,
- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],
- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T],
- N references a plurality of pulsed neurons contained in the neural network.

In a further development, the first discrimination value satisfies the following rule:

$$I(T) = -\int p(out) \cdot \ln(p(out))dt_1^{(1)} \dots dt_{k_1}^{(1)} \dots dt_{k_N}^{(N)} + \\ + \sum_{j=1}^{S} p_j \int p\left(out \middle| s^{(j)}\right) \cdot \ln\left(p\left(out \middle| s^{(j)}\right)\right) dt_1^{(1)} \dots dt_{k_1}^{(1)} \dots dt_{k_N}^{(N)} \quad (8)$$

with

$$p(out) = \sum_{j=1}^{S} p_j p\left(out \middle| s^{(j)}\right), \quad (9)$$

whereby

- $s^{(j)}$ references an input quantity that is applied to the neural network at a time j,
- p_j references a probability that the input quantity $s^{(j)}$ is applied to the neural network at a pint in time j,
- $p(out|s^{(j)})$ references a conditioned probability that a pulse is generated by a pulsed neuron in the neural network under the condition that the input quantity $s^{(j)}$ is applied to the neural network at a point in time j.

The training sequences of input quantities are preferably measured physical signals.

The methods and the arrangements can thus be utilized in the framework of the description of a technical system, particularly for describing or, respectively, investigating a multi-channel signal that has been registered by an electroencephalograph and describes an electroencephalogram.

The methods and the arrangements can also be utilized for the analysis of multi-variant financial data in a financial market for the analysis of economic relationships.

The described method steps can be realized both in software for the processor as well as in hardware, i.e. with a specific circuit.

BRIEF DESCRIPTION OF DRAWINGS

An exemplary embodiment of the invention is shown in the Figures and is explained in greater detail below.

Figure 1 is a flowchart wherein the individual method steps of the exemplary embodiment are presented;

Figure 2 is a functional block diagram showing an electroencephalograph and a patient for whom a electroencephalogram is produced;

Figure 3 is a schematic diagram of a neural network according to the exemplary embodiment;

Figure 4 is a schematic diagram on the basis whereof the principle underlying the exemplary embodiment is shown.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

Figure 2 shows a patient 200 to whose head 201 sensors 202, 203, 204, 205 and 206 are attached for the registration of brain currents. Electrical signals 207, 208, 209, 210 and 211 picked up by the sensors 202, 203, 204, 205, 206 are supplied to an electroencephalograph 220 via a first input/output interface 221. The electroencephalograph 220 comprises a plurality of input channels. Via the input/output interface 221, which is connected to an analog-to-digital converter 222, the electrical signals are supplied to the electroencephalograph 220 and digitalized in the analog-to-digital converter 222, and each registered electrical signal is stored in a memory 223 as a sequence of time row values.

A sequence of time row values is thus characterized by a sampling interval as well as by a time duration, referred to below as a time span, during which a respective electrical signal is registered. The memory 223 is connected to the analog-to-digital converter 222 as well as to a processor 224 and a second input-output interface 225 via a bus 226.

A picture screen 228 (via a first cable 227), a keyboard 230 (via a second cable 229) and a computer mouse 232 (via a third cable) are also connected to the second input/output interface 225.

Results of the examination of the patient 200 are shown on the picture screen 228. A user (not shown) can make inputs into the system via the keyboard 230 or, respectively, the computer moose 232.

The processor 224 is configured such that the method steps described later can be implemented.

A respective sequence of time row values as well as particular information about the class of time row values to which the sequence of time row values is to be allocated form a training datum.

A plurality of training data form a training data set with which a neural network 301 described later is trained.

Figure 3 shows the neural network 301 with pulsed neurons.

A sequence 306, 307 and 308 of time row values is respectively applied to a respective input neuron 302, 303 and 304 of an input layer 305. A particular information as to whether the sequence 306, 307 and 308 of the time row values, broadly referred to as input pattern 306, 307 and 308, is a matter of an input pattern 306, 307 and 308 of a first class or a matter of an input pattern 306, 307 and 308 of a second class is allocated to each applied sequence 306, 307 and 308 of time row values in the framework of the training method.

A respective input neuron 302, 303 and 304 is respectively connected to an intermediate neuron 309, 310 and 311 of an intermediate layer 312 via a weighted connection 313, 314 and 315.

The intermediate neurons 309, 310 and 311 are connected to one another via connections 316, 317, 318, 319, 320 and 321 that are likewise weighted.

The intermediate neurons 309, 310 and 311 are also connected to further pulsed neurons 322, 323 and 324 via weighted connections 325, 326, 327, 328, 329 and 330.

The pulsed neurons respectively comprise the above-described behavior that is presented in the publication by Gerstner, "Time Structure of the Activity in Neural Network Models".

The intermediate neurons 309, 310 and 311 are connected to a plurality of the intermediate neurons 309, 310 and 311; the respective, further pulsed neurons 322, 323 and 324 are respectively connected to exactly one intermediate neuron 309, 310, 311. In this way, it is possible to model a far-reaching influencing between neurons of a neural network as well as a local influencing of neurons within the neural network.

An output neuron 331 is connected to the further pulsed neurons 322, 323 and 324 via weighted connections 332, 333 and 334. The output neuron 331 forms an output signal 335 that indicates the class to which the input pattern 306, 307 and 308 belongs.

In the training phase of the neural network 301, the output quantity 335 is compared to the classification particular information allocated to the respective input pattern, and an error signal E is formed that is employed for adapting the weightings of the connections between the neurons present in the neural network 301.

The method according to the ALOPEX method, which is not gradient based, is utilized as the training method in the framework of this exemplary embodiment. The goal of the ALOPEX method is the minimization of an error criterion E taking into consideration and adapting the weightings w_{bc} for a training dataset.

The ALOPEX is explained in greater detail below.

A neuron b is connected to a neuron c via a connection that is weighted with the weighting w_{bc}. During an f^{th} iteration, the weighting w_{bc} is updated according to the following rule:

$$w_{bc}(f) = w_{bc}(f - 1) + \delta_{bc}(f), \tag{10}$$

whereby $\delta_{bc}(f)$ references a small positive or negative, predetermined step width δ according to the following rule:

$$\delta_{bc}(f) = \begin{cases} -\delta & \text{with a probability} \quad p_{bc}(f) \\ +\delta & \text{with a probability} \quad 1 - p_{bc}(f) \end{cases}. \tag{11}$$

A probability $p_{bc}(f)$ is formed according to the following rule:

$$p_{bc}(f) = \frac{1}{1 + e^{-\frac{C_{bc}(f)}{T(f)}}}, \tag{12}$$

whereby $C_{bc}(f)$ is formed according to the following rule:

$$C_{bc}(f) = \Delta w_{bc}(f) \cdot \Delta E(f). \tag{13}$$

$T(f)$ references a prescribable value. $\Delta w_{bc}(f)$ and $\Delta E(f)$ reference the weighting changes $\Delta w_{bc}(f)$ of the weightings w_{bc} or, respectively, the change $\Delta E(f)$ of the error criterion during the preceding two iterations according to the rules:

$$\Delta w_{bc}(f) = w_{bc}(f - 1) + w_{bc}(f - 2), \tag{14}$$

$$\Delta E_{bc}(f) = E_{bc}(f - 1) + E_{bc}(f - 2). \tag{15}$$

The predetermined value $T(f)$ is updated every F iterations according to the following rule:

$$T(f) = \frac{1}{FM} \sum_{b} \sum_{c} \sum_{f'=f-F}^{f-1} \left| C_{bc}(f') \right| \tag{16}$$

when f is a whole multiple of F, and

$$T(f) = T(f - 1) \quad \text{otherwise}, \tag{17}$$

whereby M references a plurality of connections in the neural network 301.

Equation (16) can be simplified to form the following rule:

$$T(f) = \frac{\delta}{F} \sum_{f'=f-F}^{f-1} \left|\Delta E(f')\right| . \tag{18}$$

The neural network 301 is trained according to the above-described training method upon employment of the training dataset.

Further, a first discrimination value I(T) for the neural network 301 is formed according to the following rule:

$$I(T) = I\left(s; \begin{Bmatrix} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{Bmatrix}\right), \tag{19}$$

whereby

- s references the input quantities,
- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],
- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T],
- N references a plurality of pulsed neurons contained in the neural network.

The first discrimination value I(T) clearly corresponds to the difference of the following entropies:

$$I(T) = H(out) - \langle H(out|s) \rangle_s , \tag{20}$$

with

$$H(out) = -\int p(out) \cdot \ln(p(out))dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)} \tag{21}$$

and

$$\langle H(out|s) \rangle_s = -\sum_{j=1}^{S} p_j \int p\left(out \middle| s^{(j)}\right) \cdot \ln\left(p\left(out \middle| s^{(j)}\right)\right) dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)} . \tag{22}$$

The first discrimination value I(T) thus derives according to the following rule:

whereby

- $s^{(j)}$ references an input quantity that is applied to the neural network at a time j,
- p_j references a probability that the input quantity $s^{(j)}$ is applied to the neural network at a pint in time j,
- $p(out|s^{(j)})$ references a conditioned probability that a pulse is generated by a pulsed neuron in the neural network under the condition that the input quantity $s^{(j)}$ is applied to the neural network at a point in time j.

When a maximum first discrimination value I(T) has been determined in the framework of training the neural network 301, then this means that the input pattern 306, 307, 308 observed in the first time span contains enough information in order to classify the input pattern with adequate dependability.

The first discrimination value I(T) is clearly formed (step 101) in the framework of the training for a first time span [0; T] (see **Figure 1**).

In a further step (step 102), a second time span is formed by shortening the first time span: [0; T'], whereby T' < T applies.

For the second time span [0; T'], a second discrimination value I(T') is formed in a further step (step 103) in the same way as described above for the first discrimination value I(T).

The first discrimination value I(T) is compared to the second discrimination value I(T') (step 104).

When the second discrimination value I(T') is the same as the first discrimination value I(T), then a new second time span is formed (step 105) by shortening the second time span [0; T'], and the new second time span is considered to be the second time span (step 106). A second discrimination value I(T') is in turn formed (step 103) for the second time span of the new iteration.

Clearly, this iterative method means that the time span wherein pulses generated by the pulsed neurons are taken into consideration for forming the output signal is shortened until the second discrimination value I(T') is unequal to the first discrimination value I(T).

When the second discrimination value I(T') is smaller than the first discrimination value, then the neural network 301 is viewed as being an optimized neural network that was trained in the last preceding iteration wherein the second discrimination value I(T') was not smaller than the first discrimination value I(T) (step 107).

The time span respectively taken into consideration is divided into discrete time sub-spans for which the only thing respectively determined is whether a neuron generated a pulse during the time sub-span or not.

In this way, the calculating outlay needed for the training is considerably reduced.

For further illustration, the principle is explained again on the basis of **Figure 4**.

Figure 4 shows two continuous processes p1 and p2 that are formed by a set of continuous input signals S1 and S2. Two sequences of input quantities, the input patterns, are present after a corresponding, above-described digitalization. The input patterns are supplied to the trained neural network 401 in an application phase, and a space-time encoding of the processes p1 and p2 is clearly implemented on the basis of the time rows for the trained neural network 401.

On the basis of an output signal 402, the trained neural network 401 indicates the kind of process the input pattern involves. The trained neural network 401 exhibits the property that, first, the dependability of the optimization is optimized and, second, a minimum plurality of time row values, i.e. a minimum second time span 403, is required in order to dependably implement the classification.

A few alternatives to the above-described exemplary embodiment are present below:

The plurality of inputs, of pulsed neurons as well as output signals is generally arbitrary. The plurality of different sequences of time row values is also arbitrary in the framework of the classification and in the framework of the training. An electroencephalogram analysis is thus possible for an arbitrary plurality of channels for characterizing tumors.

Although other modifications and changes may be suggested by those skilled in the art, it is the intention of the inventors to embody within the patent warranted hereon all changes and modifications as reasonably and properly come within the scope of their contribution to the art.

Abstract of the Disclosure

For a first time span, the neural network is trained such that a discrimination value is maximized, whereby the discrimination values is dependent on pulses that are formed by pulsed neurons within the first time span. Iteratively, the first time span is shortened and a second discrimination value is formed until the second discrimination value is smaller than the maximum discrimination value. The trained neural network is the neural network of the last iteration wherein the second discrimination value is equal to the maximum discrimination value.

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METHOD FOR TRAINING A NEURAL NETWORK, METHOD FOR THE CLASSIFICATION OF A SEQUENCE OF INPUT QUANTITIES UPON EMPLOYMENT OF A NEURAL NETWORK, NEURAL NETWORK AND ARRANGEMENT FOR THE TRAINING OF A NEURAL NETWORK

The invention is directed to a method for training a neural network, to a method for the classification of a sequence of input quantities upon employment of a neural network as well as to a neural network and an arrangement for training a neural network.

A neural network comprises neurons that are at least partially connected to one another. Input neurons of the neural network are supplied with input signals as input quantities supplied to the input neurons. The neural network usually comprises a plurality of layers. A respective neuron generates a signal dependent on input quantities supplied to a neuron of the neural network and on an activation function provided for the neuron, said signal being in turn supplied to neurons of a further layer as input quantity according to a prescribable weighting. An output quantity dependent on quantities that are supplied to the output neuron of neurons of the preceding layer is generated in an output neuron in an output layer. There are currently essentially two approaches in view of the questions as to the form in which information is stored in a neural network.

A first approach assumes that the information in a neural network is encoded in the spectral domain. Given this approach, a chronological sequence of input quantities is encoded such that a respective input neuron is provided for each time row value of a chronological sequence of the input quantities, the respective time row value being applied to this input neuron.

Given a neural network that is designed according to this approach, a hyperbolic tangent (tanh) is usually employed as activation function.

This first type of neural network is referred to below as static neural network.

What is particularly disadvantageous about this approach is that it is not possible with a static neural network to explicitly consider a dynamics of a process subject to a technical system in the internal coding of the sequence of input quantities.

The Time Delay Neural Networks (TDNN) known from [4] attempt to counter this disadvantage in that, given a plurality of sequences of input quantities, a respective input neuron is provided for each sequence and for each time row value. This approach particularly exhibits the disadvantage that the dimension of the input space -- represented by the plurality of input neurons -- increases exponentially with an increasing plurality of different sequences of input quantities to be taken into consideration.

An increasing plurality of neurons in the neural network, moreover, involves an increased training outlay upon employment of a plurality of training data that increases with an increasing plurality of neurons. A training of a static neural network becomes highly calculation-intensive under these conditions or, respectively, can practically no longer be implemented.

A gradient-based training method, for example the back-propagation method, is usually utilized for training a static neural network.

[3] also discloses a training method for a static neural network that is referred to as the ALOPEX method. In this method, the training of a static neural network is viewed as an optimization problem. In this case, the goal of the optimization is a minimization of a error criterion E taking weightings that are present in the static neural network and with which the connections between neurons are weighted into consideration for a predetermined training data set with training data.

A training datum is a tuple that [...] input quantities, for example state quantities of a technical system or, respectively, boundary conditions that a technical system is subject to and that are supplied to a technical system as well as an output quantity determined under the boundary conditions and that the technical system forms for the input quantities.

The ALOPEX method shall be explained in greater detail later in conjunction with the exemplary embodiment.

A second approach can be seen therein that the information about a system is encoded in the time domain and in the spectral domain. An artificial neural network that does justice to this approach comprises what are referred to as pulsed neurons and is known from [2].

According to [1], a pulsed neuron is modelled such that the behavior of a pulsed neuron with respect to an external stimulation, which is referred to below as input quantity, is described by a stochastic differential equation of the Itô type according to the following rule:

$$dV(t) = \left(-\frac{V(t)}{\tau} + \mu\right)dt + \sigma dW(t) + w dS(t). \tag{1}$$

In the rule (1), dW(t) references a standard Wiener process. A predetermined constant τ describes a delay of a membrane potential V(t) of the modelled neuron without input quantity that is adjacent at the neuron. The model simulates the behavior of a biological neuron. For this reason, a pulsed neuron is also referred to as biologically oriented neuron.

Further, S(t) references a coupling of the neuron with another neuron, i.e. the following applies:

$$s(t) = \frac{d}{dt} S(t) = \sum_{i} \delta(t - t_i), \tag{2}$$

whereby t_i references an arrival time at which an external impulse arrives at an input of a neuron. A soma-synaptic intensity is modelled by a synaptic quantity w.

In this model, the pulsed neuron generates a pulse when the membrane potential V(t) reaches a predetermined threshold Θ. After the pulse is generated, the membrane potential V(t) of the neuron is reset to a predetermined initialization potential value V(0).

A time sequence of pulses is thus described according to the following rule:

$$t'_0, \ldots, t'_k, \ldots, \tag{3}$$

and satisfies the following rule:

$$o(t) = \sum_k \delta\left(t - t_k'\right). \tag{4}$$

It is also known from [1] that, given the assumption of the above-described model for a pulsed neuron, a discrimination value I(T) can be formed that indicates the dependability with which a sequence of input quantities is correctly classified in view of the training data employed for a training of the neural network.

The discrimination value I(T) is dependent on pulses that are formed by the pulsed neurons within a time span [0; T] as well as on a training sequence of input quantities that are supplied to the neural network. The discrimination value I(T) satisfies the following rule:

$$I(T) = I\left(s; \begin{Bmatrix} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{Bmatrix}\right), \tag{5}$$

whereby

- s references the input quantities,
- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],
- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T],
- N references a plurality of pulsed neurons contained in the neural network.

A stochastic differential equation of the Itô type derives for a neural network with a plurality of N neurons described according to the following rule:

$$\begin{aligned} dV_i(t) = {} & \left(-\frac{V_i(t)}{\tau} + \mu\right)dt + \sigma dW_i(t) + \\ & + \sum_{j=1}^{N} w_{ij} \sum_k \delta\left(t - t_{k-\Delta_{ij}}^{(j)}\right)dt + I_i(t)dt \end{aligned}, \tag{6}$$

whereby

- V_i (t) references a membrane potential of the i^{th} neuron (i = 1, ..., N),
- N references a plurality of neurons contained in the neural network,
- w_{ij} respectively references a weighting of a coupling between the i^{th} and the j^{th} neuron, clearly a synaptic intensity between the neurons i and j,
- Δ_{ij} references a prescribable axional delay of a signal between the neurons i and j,
- $I_i(t)$ references an external stimulation signal of the neuron i.

[4] discloses a training method for a neural network. Given this method, the neural network is linked such in a control circuit with the model of a technical system that the neural network outputs at least one manipulated variable to the model as output quantity, and the model generates at least one regulating variable from the manipulated quantity supplied by the neural network, said at least one regulating variable being supplied to the neural network as input quantity. The regulating variable is superimposed with a noise having a known noise distribution before it is supplied to the model. As a reaction to the regulating variable modified by the impressed noise, the weightings of the neural network are set as follows: A cost function evaluates whether the change in weighting at the network has effected an improvement of the regulating variable with respect to a rated behavior of the model, and such weightings are favored by the cost function.

The invention is based on the problem of specifying a method as well as an arrangement for training a neural network having pulsed neurons. The invention is also based on the problem of specifying a method for the classification of a sequence of input quantities upon employment of a neural network having pulsed neurons as well as specifying a neural network having pulsed neurons.

The problems are solved by the methods and the arrangement as well as by the neural network having the features of the independent patent claims.

A method for training a neural network that contains pulsed neurons comprises the following steps:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

A method for the classification of a sequence of input quantities upon employment of a neural network that contains pulsed neurons and was trained according to the following steps comprises the following steps:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time

span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value,

-- the sequence of input quantities is supplied to the neural network;

d) a classification signal is formed that indicates what kind of sequence of input quantities the supplied sequence is.

A neural network that contains pulsed neurons has been trained according to the following steps:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

An arrangement for training a neural network that contains pulsed neurons comprises a processor that is configured such that the following steps can be implemented:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

The invention makes it possible to classify a time sequence of input quantities with a neural network what contains pulsed neurons, whereby it is assured that, given optimized classification dependability, a minimized plurality of time values must be supplied to the neural network for classification.

Preferred developments of the invention derive from the dependent claims.

An optimization method that is not gradient based is preferably employed for the maximization of the first discrimination value and/or the second discrimination value, preferably an optimization method based on the ALOPEX method.

The first discrimination value preferably satisfies the following rule:

$$I(T) = I\left(s; \left\{ \begin{matrix} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{matrix} \right\}\right), \quad (7)$$

whereby

- s references the input quantities,

- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],
- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T],
- N references a plurality of pulsed neurons contained in the neural network.

In a further development, the first discrimination value satisfies the following rule:

$$I(T) = -\int p(out) \cdot \ln(p(out))dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)} + \\ + \sum_{j=1}^{S} p_j \int p\left(out \middle| s^{(j)}\right) \cdot \ln\left(p\left(out \middle| s^{(j)}\right)\right) dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)} \tag{8}$$

with

$$p(out) = \sum_{j=1}^{S} p_j p\left(out \middle| s^{(j)}\right), \tag{9}$$

whereby

- $s^{(j)}$ references an input quantity that is applied to the neural network at a time j,
- p_j references a probability that the input quantity $s^{(j)}$ is applied to the neural network at a pint in time j,
- $p(out|s^{(j)})$ references a conditioned probability that a pulse is generated by a pulsed neuron in the neural network under the condition that the input quantity $s^{(j)}$ is applied to the neural network at a point in time j.

The training sequences of input quantities are preferably measured physical signals.

The methods and the arrangements can thus be utilized in the framework of the description of a technical system, particularly for describing or, respectively, investigating a multi-channel signal that has been registered by an electroencephalograph and describes an electroencephalogram.

The methods and the arrangements can also be utilized for the analysis of multi-variant financial data in a financial market for the analysis of economic relationships.

The described method steps can be realized both in software for the processor as well as in hardware, i.e. with a specific circuit.

An exemplary embodiment of the invention is shown in the Figures and is explained in greater detail below.

Shown are:

Figure 1 a flowchart wherein the individual method steps of the exemplary embodiment are presented;

Figure 2 a sketch of an electroencephalograph and a patient for whom a electroencephalogram is produced;

Figure 3 a sketch of a neural network according to the exemplary embodiment;

Figure 4 a sketch on the basis whereof the principle underlying the exemplary embodiment is shown.

Figure 2 shows a patient 200 to whose head 201 sensors 202, 203, 204, 205 and 206 are attached for the registration of brain stomata [sic; should probably read "currents"]. Electrical signals 207, 208, 209, 210 and 211 picked up by the sensors 202, 203, 204, 205, 206 are supplied to an electroencephalograph 220 via a first input/output interface 221. The electroencephalograph 220 comprises a plurality of input channels. Via the input/output interface 221, which is connected to an analog-to-digital converter 222, the electrical signals are supplied to the electroencephalograph 220 and digitalized in the analog-to-digital converter 222, and each registered electrical signal is stored in a memory 223 as a sequence or time row values.

A sequence of time row values is thus characterized by a sampling interval as well as by a time duration, referred to below as time span, during which a respective electrical signal is registered. The memory 223 is connected to the analog-to-digital converter 222 as well as to a processor 224 and a second input-output interface 225 via a bus 226.

A picture screen 228 (via a first cable 227), a keyboard 230 (via a second cable 229) and a computer mouse 232 (via a third cable) are also connected to the second input/output interface 225.

Results of the examination of the patient 200 are shown on the picture screen 228. A user (not shown) can make inputs into the system via the keyboard 230 or, respectively, the computer moose 232.

The processor 224 is configured such that the method steps described later can be implemented.

A respective sequence of time row values as well as a particular about the class of time row values to which the sequence of time row values is to be allocated form a training datum.

A plurality of training data form a training data set with which a neural network 301 described later is trained.

Figure 3 shows the neural network 301 with pulsed neurons.

A sequence 306, 307, 308 of time row values is respectively applied to a respective input neuron 302, 303, 304 of an input layer 305. A particular as to whether the sequence 306, 307, 308 of the time row values, broadly referred to as input pattern 306, 307, 308, is a matter of an input pattern 306, 307, 308 of a first class or a matter of an input pattern 306, 307, 308 of a second class is allocated to each applied sequence 306, 307, 308 of time row values in the framework of the training method.

A respective input neuron 302, 303, 304 is respectively connected to an intermediate neuron 309, 310, 311 of an intermediate layer 312 via a weighted connection 313, 314, 315.

The intermediate neurons 309, 310, 311 are connected to one another via connections 316, 317, 318, 319, 320, 321 that are likewise weighted.

The intermediate neurons 309, 310, 311 are also connected to further pulsed neurons 322, 323, 324 via weighted connections 325, 326, 327, 328, 329 and 330.

The pulsed neurons respectively comprise the above-described behavior that is presented in [2].

The intermediate neurons 309, 310, 311 are connected to a plurality of intermediate neurons 309, 310, 311; the respective, further pulsed neurons 322, 323, 324 are respectively connected to exactly one intermediate neuron 309, 310, 311. In this way, it is possible to model a far-reaching influencing between neurons of a neural network as well as a local influencing of neurons within the neural network.

An output neuron 331 is connected to the further pulsed neurons 322, 323, 324 via weighted connections 332, 333 and 334. The output neuron 331 forms an output signal 335 that indicates the class to which the input pattern 306, 307, 308 belongs.

In the training phase of the neural network 301, the output quantity 335 is compared to the classification particular allocated to the respective input pattern, and an error signal E is formed that is employed for adapting the weightings of the connections between the neurons present in the neural network 301.

The method according to the ALOPEX method, which is not gradient based, is utilized as the training method in the framework of this exemplary embodiment. The goal of the ALOPEX method is the minimization of an error criterion E taking into consideration and adapting the weightings w_{bc} for a training dataset.

The ALOPEX is explained in greater detail below.

A neuron b is connected to a neuron c via a connection that is weighted with the weighting w_{bc}. During an f^{th} iteration, the weighting w_{bc} is updated according to the following rule:

$$w_{bc}(f) = w_{bc}(f - 1) + \delta_{bc}(f), \qquad (10)$$

whereby $\delta_{bc}(f)$ references a small positive or negative, predetermined step width δ according to the following rule:

$$\delta_{bc}(f) = \begin{cases} -\delta & \text{with a probability} \quad p_{bc}(f) \\ +\delta & \text{with a probability} \quad 1 - p_{bc}(f) \end{cases}. \qquad (11)$$

A probability $p_{bc}(f)$ is formed according to the following rule:

$$p_{bc}(f) = \frac{1}{1 + e^{-\frac{C_{bc}(f)}{T(f)}}}, \qquad (12)$$

whereby $C_{bc}(f)$ is formed according to the following rule:

$$C_{bc}(f) = \Delta w_{bc}(f) \cdot \Delta E(f). \qquad (13)$$

T(f) references a prescribable value. $\Delta w_{bc}(f)$ and $\Delta E(f)$ reference the weighting changes $\Delta w_{bc}(f)$ of the weightings w_{bc} or, respectively, the change $\Delta E(f)$ of the error criterion during the preceding two iterations according to the rules:

$$\Delta w_{bc}(f) = w_{bc}(f - 1) + w_{bc}(f - 2), \qquad (14)$$

$$\Delta E_{bc}(f) = E_{bc}(f - 1) + E_{bc}(f - 2). \qquad (15)$$

The predetermined value T(f) is updated every F iterations according to the following rule:

$$T(f) = \frac{1}{FM} \sum_{b} \sum_{c} \sum_{f'=f-F}^{f-1} \left|C_{bc}(f')\right| \qquad (16)$$

when f is a whole multiple of F, and

$$T(f) = T(f - 1) \quad \text{otherwise}, \qquad (17)$$

whereby M references a plurality of connections in the neural network 301.

Equation (16) can be simplified to form the following rule:

$$T(f) = \frac{\delta}{F} \sum_{f'=f-F}^{f-1} \left|\Delta E(f')\right|. \qquad (18)$$

The neural network 301 is trained according to the above-described training method upon employment of the training dataset.

Further, a first discrimination value I(T) for the neural network 301 is formed according to the following rule:

$$I(T) = I\left(s; \left\{\begin{matrix} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{matrix}\right\}\right), \quad (19)$$

whereby

- s references the input quantities,
- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],
- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T],
- N references a plurality of pulsed neurons contained in the neural network.

The first discrimination value I(T) clearly corresponds to the difference of the following entropies:

$$I(T) = H(out) - \langle H(out|s)\rangle_s, \quad (20)$$

with

$$H(out) = -\int p(out) \cdot \ln(p(out))dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)} \quad (21)$$

and

$$\langle H(out|s)\rangle_s = -\sum_{j=1}^{S} p_j \int p\left(out \middle| s^{(j)}\right) \cdot \ln\left(p\left(out \middle| s^{(j)}\right)\right)dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)}. \quad (22)$$

The first discrimination value I(T) thus derives according to the following rule:

$$I(T) = -\int p(out) \cdot \ln(p(out)) dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)} + \\ + \sum_{j=1}^{S} p_j \int p\left(out \middle| s^{(j)}\right) \cdot \ln\left(p\left(out \middle| s^{(j)}\right)\right) dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)} \tag{23}$$

with

$$p(out) = \sum_{j=1}^{S} p_j p\left(out \middle| s^{(j)}\right), \tag{24}$$

whereby

- $s^{(j)}$ references an input quantity that is applied to the neural network at a time j,
- p_j references a probability that the input quantity $s^{(j)}$ is applied to the neural network at a pint in time j,
- $p(out|s^{(j)})$ references a conditioned probability that a pulse is generated by a pulsed neuron in the neural network under the condition that the input quantity $s^{(j)}$ is applied to the neural network at a point in time j.

When a maximum first discrimination value I(T) has been determined in the framework of training the neural network 301, then this means that the input pattern 306, 307, 308 observed in the first time span contains enough information in order to classify the input pattern with adequate dependability.

The first discrimination value I(T) is clearly formed (step 101) in the framework of the training for a first time span [0; T] (see **Figure 1**).

In a further step (step 102), a second time span is formed by shortening the first time span: [0; T'], whereby T' < T applies.

For the second time span [0; T'], a second discrimination value I(T') is formed in a further step (step 103) in the same way as described above for the first discrimination value I(T).

The first discrimination value I(T) is compared to the second discrimination value I(T') (step 104).

When the second discrimination value I(T') is the same as the first discrimination value I(T), then a new second time span is formed (step 105) by shortening the second time span [0; T'], and the new second time span is considered to be the second time span (step 106). A second discrimination value I(T') is in turn formed (step 103) for the second time span of the new iteration.

Clearly, this iterative method means that the time span wherein pulses generated by the pulsed neurons are taken into consideration for forming the output signal is shortened until the second discrimination value I(T') is unequal to the first discrimination value I(T).

When the second discrimination value I(T') is smaller than the first discrimination value, then the neural network 301 is viewed as being an optimized neural network that was trained in the last preceding iteration wherein the second discrimination value I(T') was not smaller than the first discrimination value I(T) (step 107).

The time span respectively taken into consideration is divided into discrete time sub-spans for which the only thing respectively determined is whether a neuron generated a pulse during the time sub-span or not.

In this way, the calculating outlay needed for the training is considerably reduced.

For further illustration, the principle is explained again on the basis of **Figure 4**.

Figure 4 shows two continuous processes p1 and p2 that are formed by a set of continuous input signals S1 and S2. Two sequences of input quantities, the input patterns, are present after a corresponding, above-described digitalization. The input patterns are supplied to the trained neural network 401 in an application phase, and a space-time encoding of the processes p1, p2 is clearly implemented on the basis of the time rows for the trained neural network 401.

On the basis of an output signal 402, the trained neural network 401 indicates the kind of process the input pattern involves. The trained neural network 401 exhibits the property that, first, the dependability of the optimization is optimized

and, second, a minimum plurality of time row values, i.e. a minimum second time span 403, is required in order to dependably implement the classification.

A few alternatives to the above-described exemplary embodiment are present below:

The plurality of inputs, of pulsed neurons as well as output signals is generally arbitrary. The plurality of different sequences of time row values is also arbitrary in the framework of the classification and in the framework of the training. An electroencephalogram analysis is thus possible for an arbitrary plurality of channels for characterizing tumors.

The following publications have been cited in this document:

[1] G. Deco and B. Schürmann, Information Transmission and Temporal Code in Central Spiking Neurons, Physical Review Letters, Vol. 79, No. 23, pp. 4697-4700, December 1997

[2] W. Gerstner, Time structure of the activity in neural network models, Physical Review E, Vol. 51, No. 1, pp. 738-758, January 1995

[3] K. P. Unnikrishnan and K. P. Venugopal, Alopex: A Correlation-Based Learning Algorithm for Feedforward and Recurrent Neural Networks, pp. 471-490, Neural Computation, Vol. 6, 1994

[4] DE 195 31 967 C2

Patent Claims

1. Method for training a neural network that contains pulsed neurons,

a) the neural network is trained such for a first time span ([0; T]) that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

2. Method according to claim 1, whereby an optimization method that is not gradient based is utilized for the maximization of the first discrimination value and/or of the second discrimination value.

3. Method according to claim 2, whereby the optimization method is based on the ALOPEX method.

4. Method according to one of the claims 1 through 3, whereby the first discrimination value I(T) satisfies the following rule:

$$I(T) = I\left(s; \begin{Bmatrix} t_1^{(1)}, \ldots, t_m^{(1)}, \ldots, t_{k_1}^{(1)}, t_1^{(2)}, \ldots, t_m^{(2)}, \ldots, t_{k_2}^{(2)}, \ldots, \\ t_1^{(n)}, \ldots, t_m^{(n)}, \ldots, t_{k_n}^{(n)}, \ldots, t_1^{(N)}, \ldots, t_m^{(N)}, \ldots, t_{k_N}^{(N)} \end{Bmatrix}\right),$$

whereby

- s references the input quantities,

- $t_m^{(n)}$ references a pulse that is generated by a pulsed neuron n at a time m within a time span [0, T],
- k_n (n = 1, ..., N) references a point in time at which the pulsed neuron n has generated the last pulse within the time span [0, T],
- N references a plurality of pulsed neurons contained in the neural network.

5. Method according to claim 4, whereby the first discrimination value I(T) satisfies the following rule:

$$I(T) = -\int p(out) \cdot \ln(p(out)) dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)} + \\ + \sum_{j=1}^{S} p_j \int p\left(out \middle| s^{(j)}\right) \cdot \ln\left(p\left(out \middle| s^{(j)}\right)\right) dt_1^{(1)} \ldots dt_{k_1}^{(1)} \ldots dt_{k_N}^{(N)}$$

with

$$p(out) = \sum_{j=1}^{S} p_j p\left(out \middle| s^{(j)}\right),$$

whereby

- $s^{(j)}$ references an input quantity that is applied to the neural network at a time j,
- p_j references a probability that the input quantity $s^{(j)}$ is applied to the neural network at a pint in time j,
- $p(out|s^{(j)})$ references a conditioned probability that a pulse is generated by a pulsed neuron in the neural network under the condition that the input quantity $s^{(j)}$ is applied to the neural network at a point in time j.

6. Method according to one of the claims 1 through 5, whereby the training sequence of inputs quantities are [sic] measured physical signals.

7. Method according to claim 6, whereby the training sequence of input quantities are [sic] signals of an electroencephalogram.

8. Method for the classification of a sequence of input quantities upon employment of a neural network that contains pulsed neurons and was trained according to the following steps:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value,

-- whereby the sequence of input quantities is supplied to the neural network;

-- whereby a classification signal is formed that indicates what kind of sequence of input quantities the supplied sequence is.

9. Method according to claim 9, whereby the training sequence of input quantities and the sequence of input quantities are measured physical signals.

10. Method according to claim 9, whereby the training sequence of input quantities and the sequence of input quantities are measured signals of an electroencephalogram.

11. Neural network that contains pulsed neurons has been trained according to the following steps:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

12. Neural network according to claim 10, utilized for the classification of a physical signal.

13. Neural network according to claim 10, utilized for the classification of a physical signal.

14. Arrangement for training a neural network that contains pulsed neurons comprises a processor that is configured such that the following steps can be implemented:

a) the neural network is trained such for a first time span that a discrimination value is maximized, as a result whereof a maximum first discrimination value is formed;

b) the discrimination value is formed dependent on pulses that are formed by the pulsed neurons within the first time span as well as on a training sequence of input quantities that are supplied to the neural network;

c) the following steps are interactively implemented:

-- the first time span is shortened to form a second time span,

-- a second discrimination value is formed for the second time span,

-- when the second discrimination value is the same as the first discrimination value, then a new iteration ensues with a new second time span that is formed by shortening the second time span of the preceding iteration,

-- otherwise, the method is ended and the trained neural network is the neural network of the last iteration wherein the second discrimination value is the same as the first discrimination value.

15. Arrangement according to claim 14, utilized for the classification of a physical signal.

16. Arrangement according to claim 14, utilized for the classification of a signal of an electroencephalogram.

Abstract

METHOD FOR TRAINING A NEURAL NETWORK, METHOD FOR THE CLASSIFICATION OF A SEQUENCE OF INPUT QUANTITIES UPON EMPLOYMENT OF A NEURAL NETWORK, NEURAL NETWORK AND ARRANGEMENT FOR THE TRAINING OF A NEURAL NETWORK

For a first time span, the neural network is trained such that a discrimination value is maximized, whereby the discrimination values is dependent on pulses that are formed by pulsed neurons within the first time span. Iteratively, the first time span is shortened and a second discrimination value is formed until the second discrimination value is smaller than the maximum discrimination value. The trained neural network is the neural network of the last iteration wherein the second discrimination value is equal to the maximum discrimination value.

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(54) Title: METHOD FOR TRAINING A NEURAL NETWORK, METHOD FOR CLASSIFYING A SEQUENCE OF INPUT PARAMETERS USING A NEURAL NETWORK, NEURAL NETWORK AND ARRAY FOR TRAINING A NEURAL NETWORK

(54) Bezeichnung: VERFAHREN ZUM TRAINIEREN EINES NEURONALEN NETZES, VERFAHREN ZUR KLASSIFIKATION EINER FOLGE VON EINGANGSGRÖSSEN UNTER VERWENDUNG EINES NEURONALEN NETZES, NEURONALES NETZ UND ANORDNUNG ZUM TRAINIEREN EINES NEURONALEN NETZES

(57) Abstract

The neural network is trained for a first period in such a way that a discrimination value is maximized, wherein the discrimination value is dependent on impulses formed by the pulsed neurons during the first period. The first period is shortened in an iterative manner and a second discrimination value is formed for the second period until the second discrimination value is smaller than the maximum discrimination value. The trained neural network is the neural network of the last iteration in which the second discrimination value equals the maximum discrimination value.

(57) Zusammenfassung

Für einen ersten Zeitraum wird das neuronale Netz derart trainiert, daß ein Unterscheidungswert maximiert wird, wobei der Unterscheidungswert abhängig ist von Impulsen, die von den gepulsten Neuronen innerhalb des ersten Zeitraums gebildet werden. Iterativ wird der erste Zeitraum so lange verkürzt und für den zweiten Zeitraum ein zweiter Unterscheidungswert gebildet, bis der zweite Unterscheidungswert kleiner ist als der maximale Unterscheidungswert. Das trainierte neuronale Netz ist das neuronale Netz der letzten Iteration, bei der der zweite Unterscheidungswert gleich dem maximalen Unterscheidungswert ist.

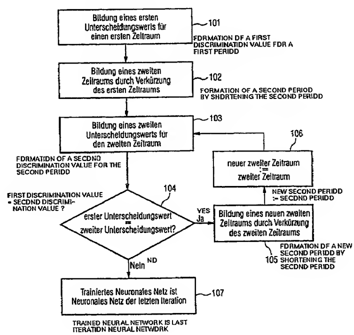

FIG 1

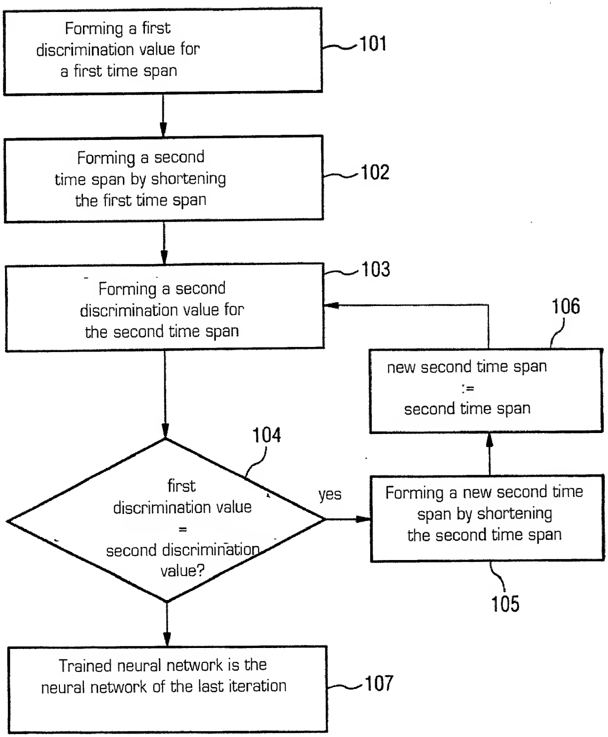
Forming a first discrimination value for a first time span
101
Forming a second time span by shortening the first time span
102
Forming a second discrimination value for the second time span
103
106
new second time span := second time span
104
first discrimination value = second discrimination value?
yes
Forming a new second time span by shortening the second time span
105
Trained neural network is the neural network of the last iteration
107

FIG 2

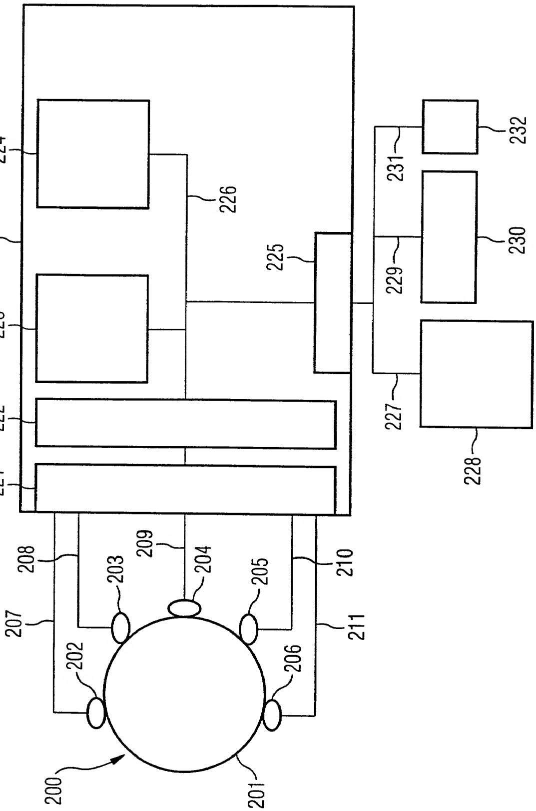
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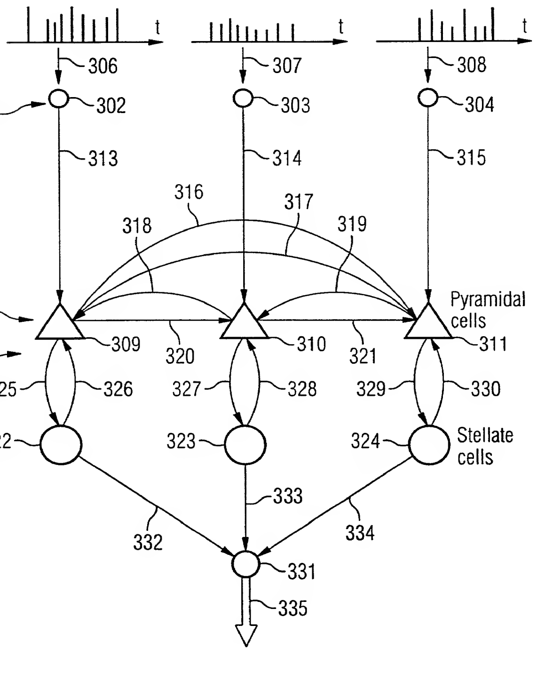
FIG 3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322
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Stellate cells
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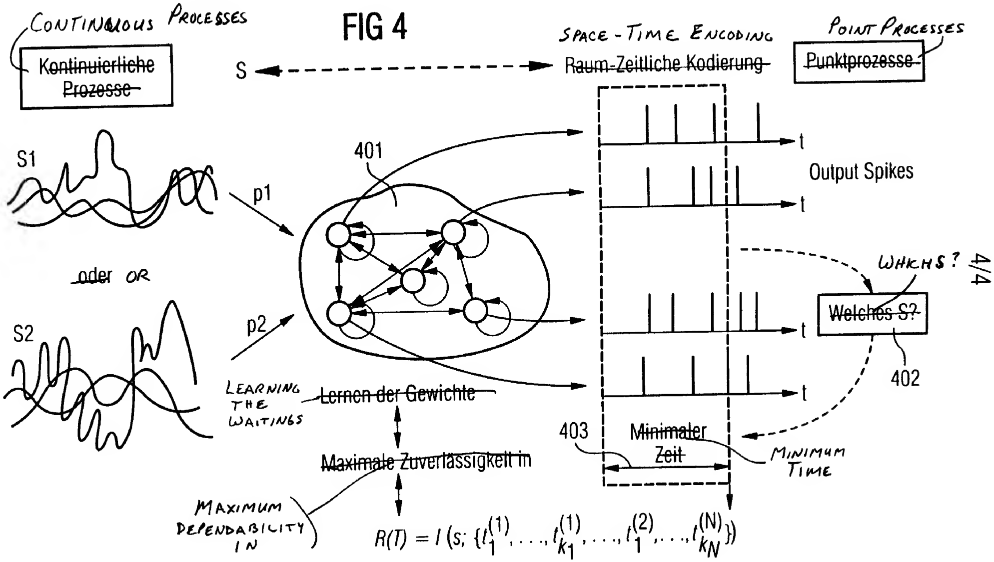
332
334
331
335

FIG 4


CONTINUOUS PROCESSES
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SPACE - TIME ENCODING
POINT PROCESSES
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p1
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WHICH S?
~~Welches S?~~
402
403
~~Minimaler Zeit~~
MINIMUM TIME
LEARNING THE WAITINGS
~~Lernen der Gewichte~~
~~Maximale Zuverlässigkeit in~~
MAXIMUM DEPENDABILITY IN
$R(T) = I\,(s;\ \{t_1^{(1)}, \ldots, t_{k_1}^{(1)}, \ldots, t_1^{(2)}, \ldots, t_{k_N}^{(N)}\})$

German Language Declaration

VERTRETUNGSVOLLMACHT: Als benannter Erfinder beauftrage ich hiermit den nachstehend benannten Patentanwalt (oder die nachstehend benannten Patentanwälte) und/oder Patent-Agenten mit der Verfolgung der vorliegenden Patentanmeldung sowie mit der Abwicklung aller damit verbundenen Geschäfte vor dem Patent- und Warenzeichenamt: *(Name und Registrationsnummer anführen)*

POWER OF ATTORNEY: As a named inventor, I hereby appoint the following attorney(s) and/or agent(s) to prosecute this application and transact all business in the Patent and Trademark Office connected therewith. *(list name and registration number)*

And I hereby appoint

Messrs. John D. Simpson (Registration No. 19,842) Lewis T. Steadman (17,074), William C. Stueber (16,453), P. Phillips Connor (19,259), Dennis A. Gross (24,410), Marvin Moody (16,549), Steven H. Noll (28,982), Brett A. Valiquet (27,841), Thomas I. Ross (29,275), Kevin W. Guynn (29,927), Edward A. Lehmann (22,312), James D. Hobart (24,149), Robert M. Barrett (30,142), James Van Santen (16,584), J. Arthur Gross (13,615), Richard J. Schwarz (13,472) and Melvin A. Robinson (31,870), David R. Metzger (32,919), John R. Garrett (27,888) all members of the firm of Hill, Steadman & Simpson, A Professional Corporation.

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Unterschrift des Erfinders — Datum: 14.6.99	Inventor's signature — Date
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(Bitte entsprechende Informationen und Unterschriften im Falle von dritten und weiteren Miterfindern angeben).

(Supply similar information and signature for third and subsequent joint inventors).

Form PTO-FB-240 (8-83) Patent and Trademark Office-U.S. Department of COMMERCE

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Prior foreign appplications
Priorität beansprucht

			Priority Claimed	
198 38 654.0	Germany	25. August 1998	☒	☐
(Number) (Nummer)	(Country) (Land)	(Day Month Year Filed) (Tag Monat Jahr eingereicht)	Yes Ja	No Nein
			☐	☐
(Number) (Nummer)	(Country) (Land)	(Day Month Year Filed) (Tag Monat Jahr eingereicht)	Yes Ja	No Nein
			☐	☐
(Number) (Nummer)	(Country) (Land)	(Day Month Year Filed) (Tag Monat Jahr eingereicht)	Yes Ja	No Nein

Ich beanspruche hiermit gemäss Absatz 35 der Zivilprozessordnung der Vereinigten Staaten, Paragraph 120, den Vorzug aller unten aufgeführten Anmeldungen und falls der Gegenstand aus jedem Anspruch dieser Anmeldung nicht in einer früheren amerikanischen Patentanmeldung laut dem ersten Paragraphen des Absatzes 35 der Zivilprozeßordnung der Vereinigten Staaten, Paragraph 122 offenbart ist, erkenne ich gemäss Absatz 37, Bundesgesetzbuch, Paragraph 1.56(a) meine Pflicht zur Offenbarung von Informationen an, die zwischen dem Anmeldedatum der früheren Anmeldung und dem nationalen oder PCT internationalen Anmeldedatum dieser Anmeldung bekannt geworden sind.

I hereby claim the benefit under Title 35. United States Code. §120 of any United States application(s) listed below and, insofar as the subject matter of each of the claims of this application is not disclosed in the prior United States application in the manner provided by the first paragraph of Title 35, United States Code, §122, I acknowledge the duty to disclose material information as defined in Title 37, Code of Federal Regulations, §1.56(a) which occured between the filing date of the prior application and the national or PCT international filing date of this application.

(Application Serial No.) (Anmeldeseriennummer)	(Filing Date) (Anmeldedatum)	(Status) (patentiert, anhängig, aufgegeben)	(Status) (patented, pending, abandoned)
(Application Serial No.) (Anmeldeseriennummer)	(Filing Date) (Anmeldedatum)	(Status) (patentiert, anhängig, aufgegeben)	(Status) (patented, pending, abandoned)

Ich erkläre hiermit, dass alle von mir in der vorliegenden Erklärung gemachten Angaben nach meinem besten Wissen und Gewissen der vollen Wahrheit entsprechen, und dass ich diese eidesstattliche Erklärung in Kenntnis dessen abgebe, dass wissentlich und vorsätzlich falsche Angaben gemäss Paragraph 1001, Absatz 18 der Zivilprozessordnung der Vereinigten Staaten von Amerika mit Geldstrafe belegt und/oder Gefängnis bestraft werden koennen, und dass derartig wissentlich und vorsätzlich falsche Angaben die Gültigkeit der vorliegenden Patentanmeldung oder eines darauf erteilten Patentes gefährden können.

I hereby declare that all statements made herein of my own knowledge are true and that all statements made on information and belief are believed to be true, and further that these statements were made with the knowledge that willful false statements and the like so made are punishable by fine or imprisonment, or both, under Section 1001 of Title 18 of the United States Code and that such willful false statements may jeopardize the validity of the application or any patent issued thereon.

Declaration and Power of Attorney For Patent Application

Erklärung Für Patentanmeldungen Mit Vollmacht

German Language Declaration

Als nachstehend benannter Erfinder erkläre ich hiermit an Eides Statt:

As a below named inventor, I hereby declare that:

dass mein Wohnsitz, meine Postanschrift, und meine Staatsangehörigkeit den im Nachstehenden nach meinem Namen aufgeführten Angaben entsprechen,

My residence, post office address and citizenship are as stated below next to my name,

dass ich, nach bestem Wissen der ursprüngliche, erste und alleinige Erfinder (falls nachstehend nur ein Name angegeben ist) oder ein ursprünglicher, erster und Miterfinder (falls nachstehend mehrere Namen aufgeführt sind) des Gegenstandes bin, für den dieser Antrag gestellt wird und für den ein Patent beantragt wird für die Erfindung mit dem Titel:

I believe I am the original, first and sole inventor (if only one name is listed below) or an original, first and joint inventor (if plural names are listed below) of the subject matter which is claimed and for which a patent is sought on the invention entitled

Verfahren zum Trainieren eines neuronalen Netzes, Verfahren zur Klassifikation einer Folge von Eingangsgrößen unter Verwendung eines neuronalen Netzes, neuronales Netz und Anordnung zum Trainieren eines neuronalen Netzes

____

deren Beschreibung

the specification of which

(zutreffendes ankreuzen)

(check one)

☒ hier beigefügt ist.

☐ is attached hereto.

☐ am ____________ als PCT internationale Anmeldung PCT Anmeldungsnummer ____________ eingereicht wurde und am ____________ abgeändert wurde (falls tatsächlich abgeändert).

☐ was filed on ____________ as PCT international application PCT Application No ____________ and was amended on ____________ (if applicable)

Ich bestätige hiermit, dass ich den Inhalt der obigen Patentanmeldung einschliesslich der Ansprüche durchgesehen und verstanden habe, die eventuell durch einen Zusatzantrag wie oben erwähnt abgeandert wurde.

I hereby state that I have reviewed and understand the contents of the above identified specification, including the claims as amended by any amendment referred to above.

Ich erkenne meine Pflicht zur Offenbarung irgendwelcher Informationen, die für die Prüfung der vorliegenden Anmeldung in Einklang mit Absatz 37, Bundesgesetzbuch, Paragraph 1.56(a) von Wichtigkeit sind, an.

I acknowledge the duty to disclose information which is material to the examination of this application in accordance with Title 37, Code of Federal Regulations, §1.56(a).

Ich beanspruche hiermit ausländische Prioritatsvorteile gemäss Abschnitt 35 der Zivilprozessordnung der Vereinigten Staaten, Paragraph 119 aller unten angegebenen Auslandsanmeldungen für ein Patent oder eine Erfindersurkunde, und habe auch alle Auslandsanmeldungen für ein Patent oder eine Erfindersurkunde nachstehend gekennzeichnet, die ein Anmeldedatum haben, das vor dem Anmeldedatum der Anmeldung liegt, für die Priorität beansprucht wird.

I hereby claim foreign priority benefits under Title 35, United States Code, §119 of any foreign application(s) for patent or inventor's certificate listed below and have also identified below any foreign application for patent or inventor's certificate having a filing date before that of the application on which priority is claimed: